Analyzing Visualization Workload through Leverage Points

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Objectiv

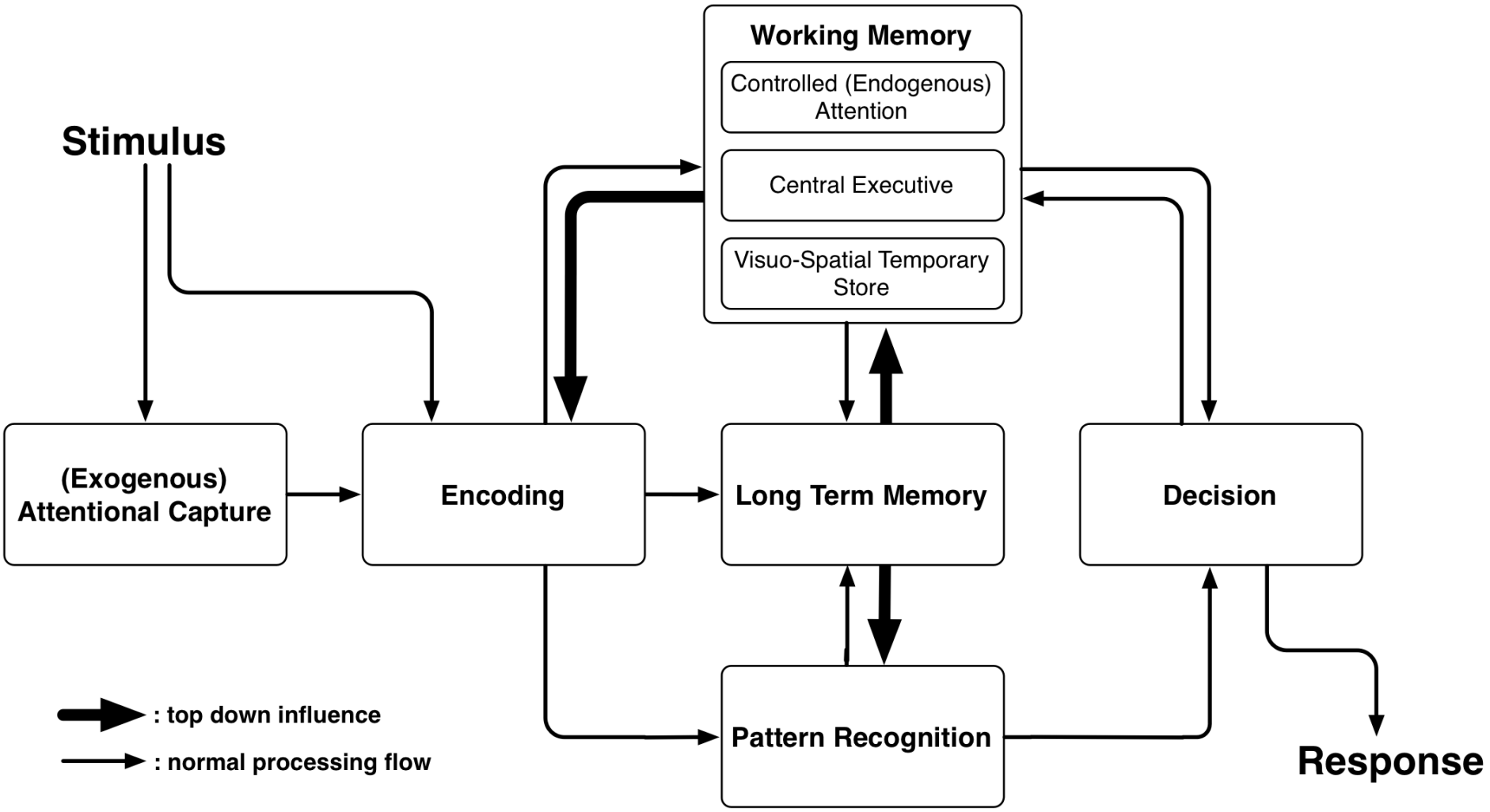
- Analyze workload that visual data representations place on users
- Find methods to reduce this workload

Approac

- Use theory of *leverage points* to identify techniques that will reduce workload
- Validate this approach by analyzing results from user studies

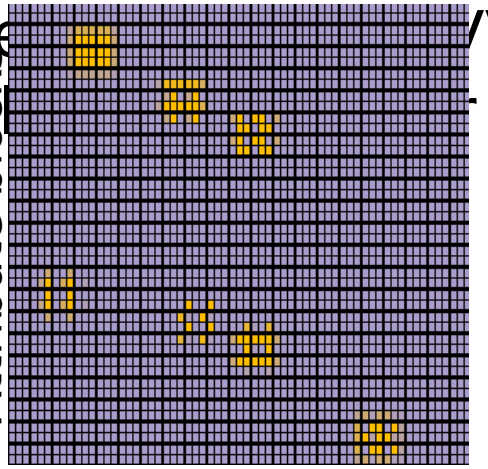
What are Leverage Points

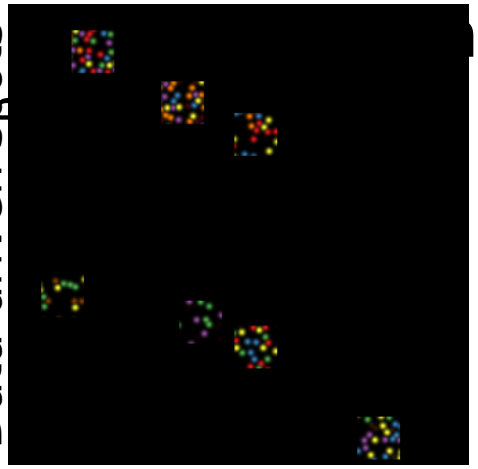
Patterson et al. (2014) define *leverage points* in the information visualization design process as access **mechanisms** which encourage a designer to choose visualization parameters **that will improve knowledge extraction**. The leverage points are derived from knowledge of the cognitive system in order to influence attention and memory. All the leverage points are specific to an underlying cognitive process or to the interaction between cognitive processes.

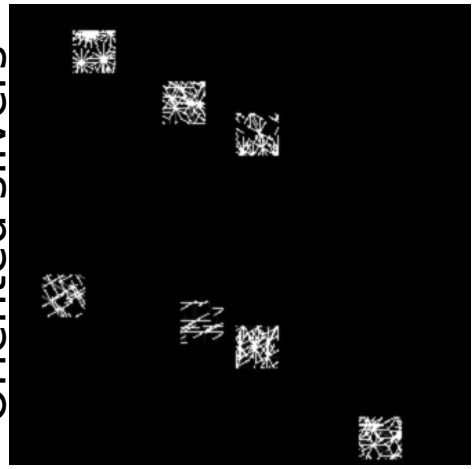

Working Memory
Controlled (Endogenous) Attention
Central Executive
Visuo-Spatial Temporary Store
Stimulus
(Exogenous) Attentional Capture
Encoding
Long Term Memory
Decision
Pattern Recognition
Response
: top down influence
: normal processing flow

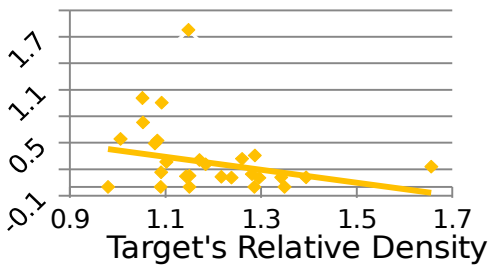
1. Use salient cues to direct exogenous

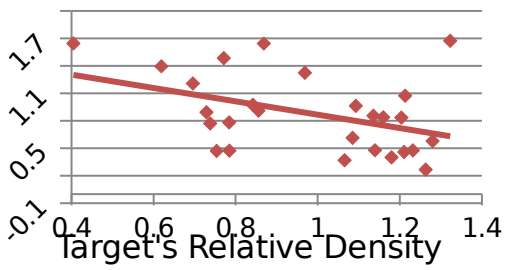
Exogenous attention may be directed by varying color or texture [V.] density, correlation, or error

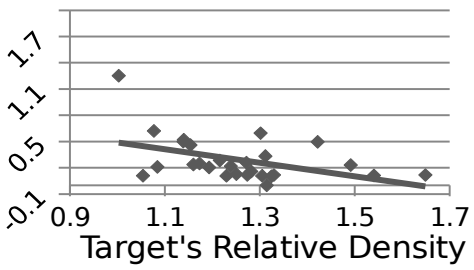


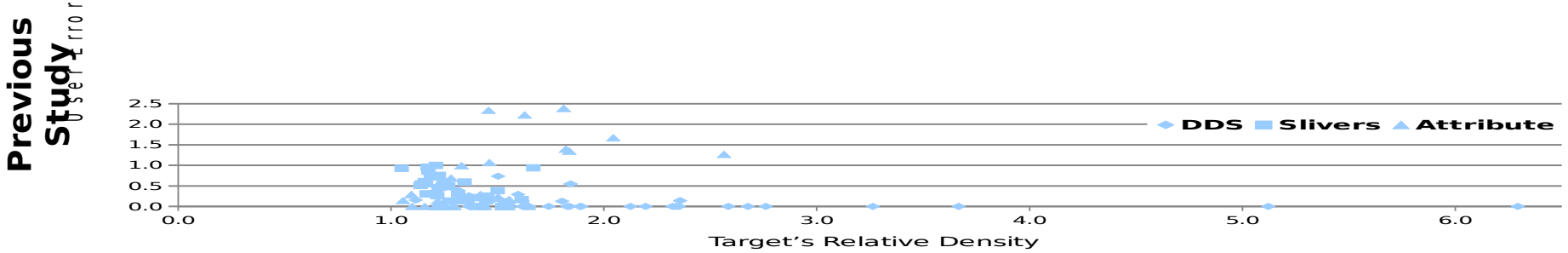








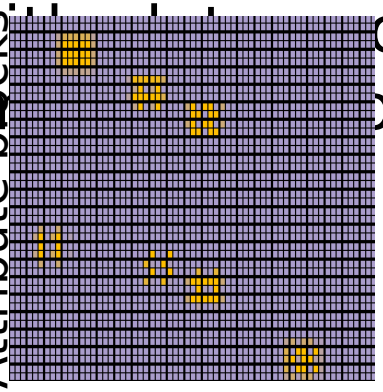




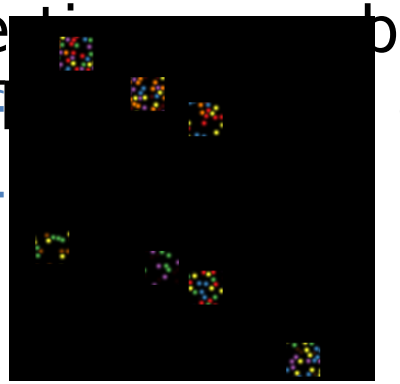
2. Provide strong grouping cues for

Working memory has a limited capacity, but the contents can be facts or concepts. Knowledge structures, such as patterns in a visualization that may be associated with [illegible] can be retrieved from long-term [illegible] similar encoding.

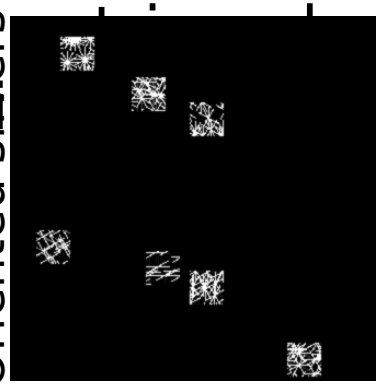
Attribute blocks



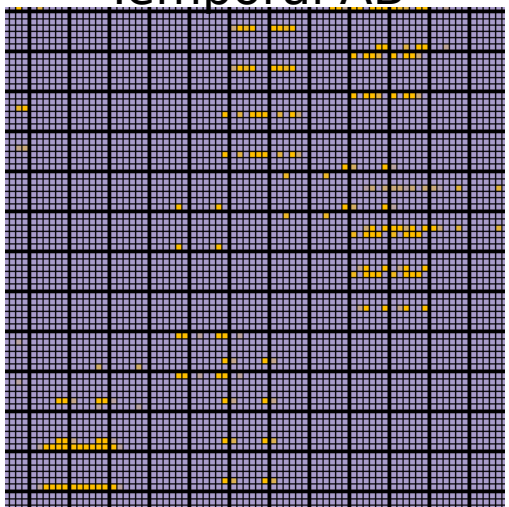
Data-driven spots



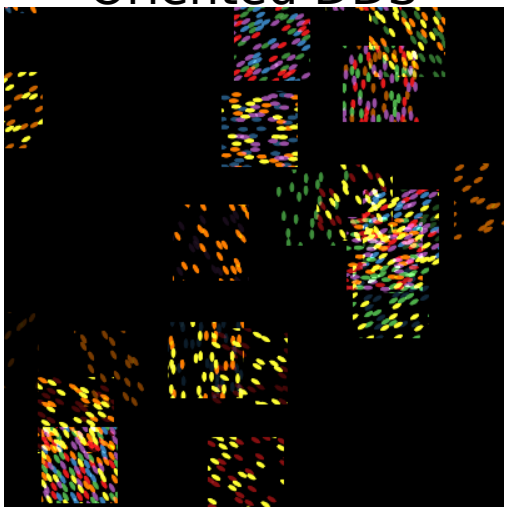
Oriented slivers

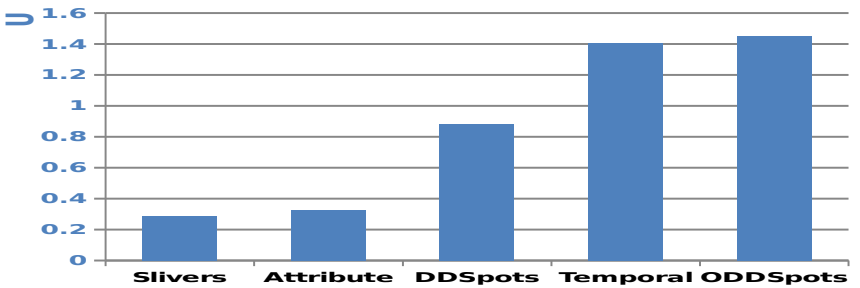


Temporal AB



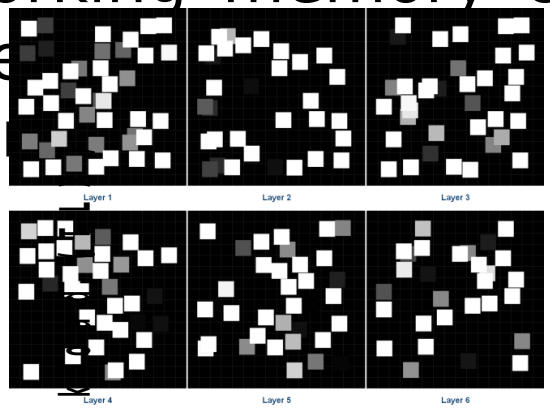
Oriented DDS

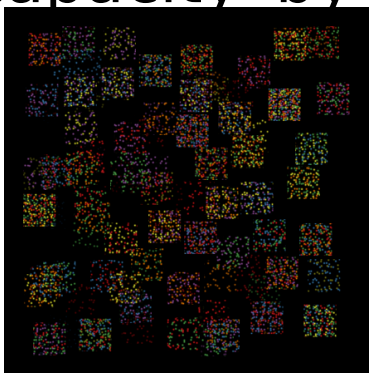


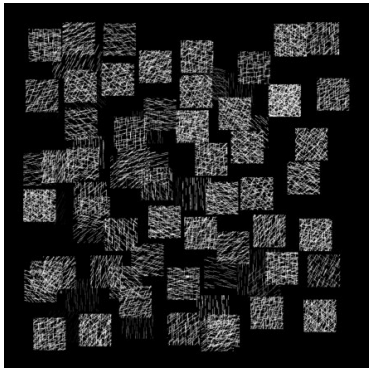


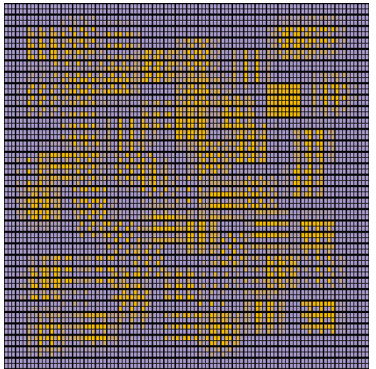
3. Provide strong grouping cues to facilitate

Reduce competition for working memory capacity by helping user to group piece
"chunks." Assist this by pe





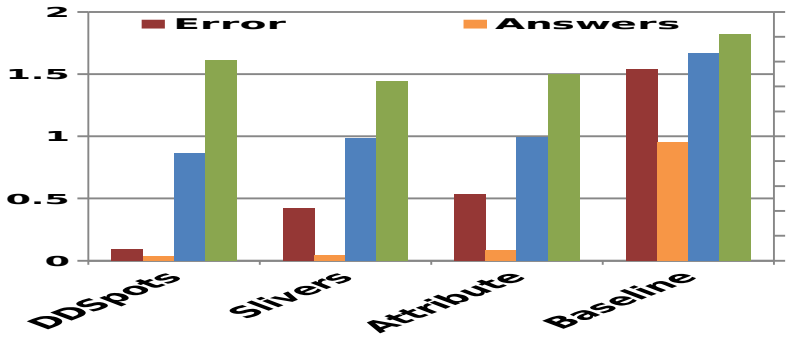




Error (Target Layers) and Number of Changes to A

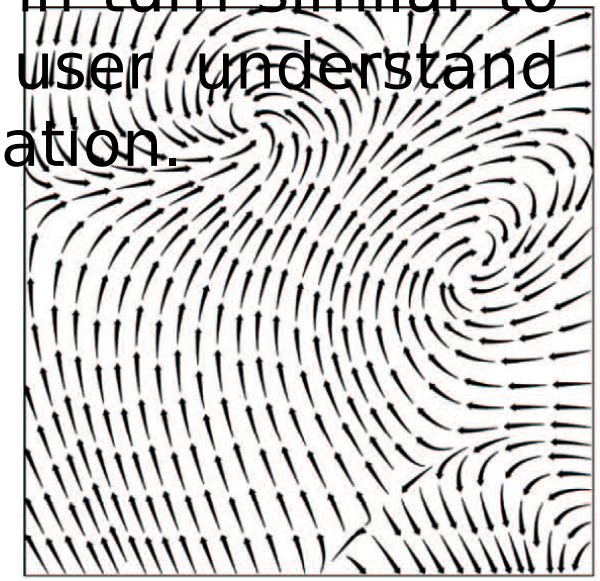
Time (sec) and Work

70
50
30
20
10



4. Organize information for knowledge

Help user recall mental models, which involve possibilities and projection; these are in turn similar to sense-making. This should help a user understand data and turn it into actionable information.



Unfortunately, tasks in most user studies of multivariate visualization are quite low-level and performed by novice users. Laidlaw et al. (2005) found that image-guided streamline placement assisted in advection of particles and identification of critical point type.

This follows from the leverage point, since streamlines guide even novice users to the proper mental model of flow through the field, which is critical to each

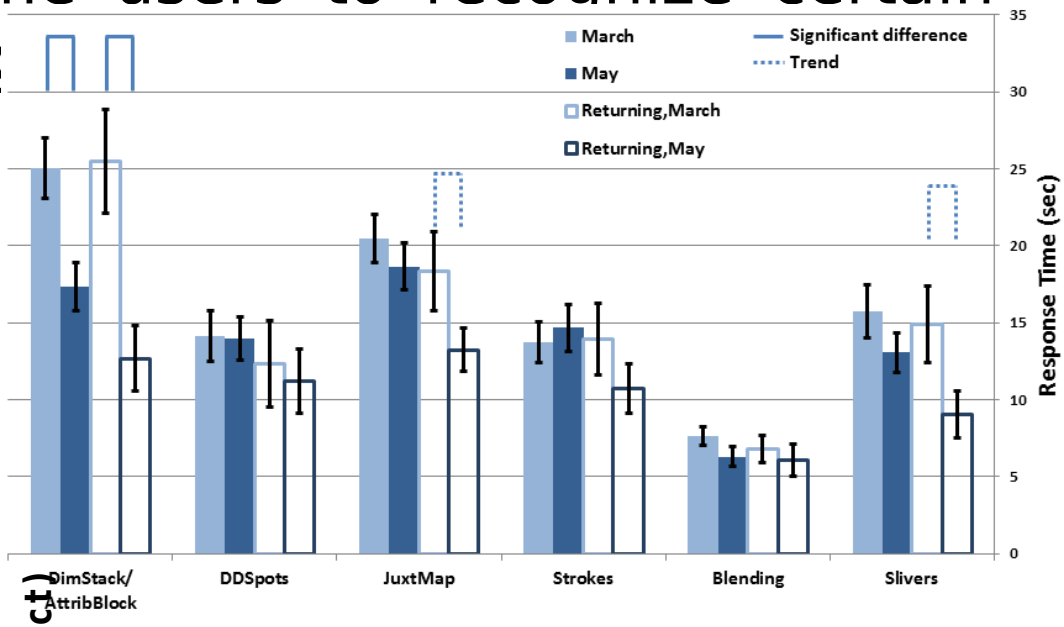
Tasks in Multivariate Visualization User Studies
Identify critical point type **Advect particle**
Localize critical values
Read sequence of data values
Detect greatest trends
Detect multi-way overlap

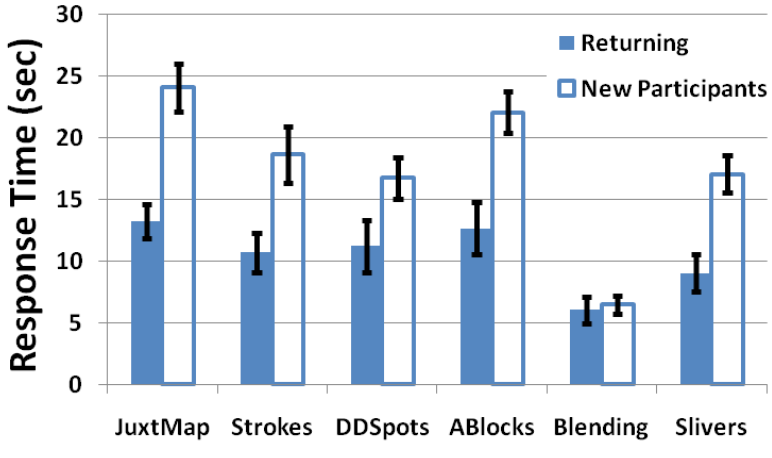
5. Structure information to provide strong

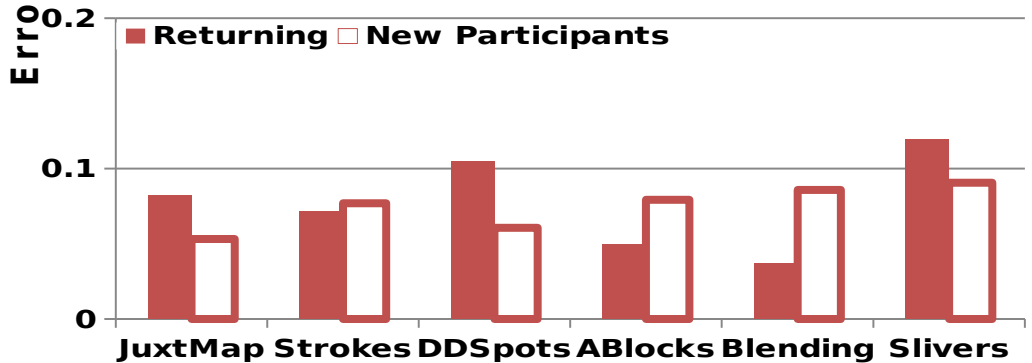
Structure information to provide strong retrieval cues for mental models to help analogical reasoning. Enable user to apply prior knowledge to new data patterns.

6. Develop training regimes for implicit

Statistical regularities may be learned implicitly; thus, visualizations could prime users to recognize certain data relationships throu
may be recognized.







Conclusions

- Appear to be validated by the empirical evidence:
  - Exogenous attention
  - Grouping cues that facilitate chunking
- May have some indirect evidence in the empirical data:
  - Grouping cues for information
  - Organization based on mental models
  - Training for implicit learning
- Not supported by currently available data:
  - Structuring information to link to mental models

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